Predicting Suicide Attacks: A Fuzzy Soft Set Approach

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Abstract. This paper models a decision support system to predict the occurance of suicide attack in a given collection of cities. The system comprises two parts. First part analyzes and identifies the factors which affect the prediction. Admitting incomplete information and use of linguistic terms by experts, as two characteristic features of this peculiar prediction problem we exploit the Theory of Fuzzy Soft Sets. Hence the Part 2 of the model is an algorithm vz. FSP which takes the assessment of factors given in Part 1 as its input and produces a possibility profile of cities likely to receive the accident. The algorithm is of $O(2^n)$ complexity. It has been illustrated by an example solved in detail. Simulation results for the algorithm have been presented which give insight into the strengths and weaknesses of FSP. Three different decision making measures have been simulated and compared in our discussion.

Keywords: Decision support; fuzzy soft set; suicide attack; counter-terror strategy

1. Introduction

As this paper was in final stage of preparation, on July 2, 2010 two simultaneous suicide attacks took place in the Pakistani cosmopolitan city of Lahore. The attacks left 50 innocent people killed instantly and another 200 severely injured. In total, since 9/11 some 247 suicide attacks took place in Pakistan killing more than 3000 people. Suicide attacks, when people themselves are weapons for destruction, have risen globally from an average of about 3 per year in the 1980s to 40 a year in 2002, almost 50 a year in 2005 and more than 200 by 2009-10. Globally three fourth of all suicide bombings have happened since the terror attacks in the USA on September 11, 2001. Altogether in 16 countries over 300 suicide attacks have resulted in more than 5,300 people killed and over 10,000 wounded.

In the typical modus operandi of suicide attacks, the terrorist wears an explosive belt on the body or carries it in a suitcase, sports bag, or rucksack. Such charges are usually stuffed with about 3–15 kg of TNT or homemade explosives, together with small chunks of iron or a large quantity of nails packed around explosives, in order to maximize casualties and loss of limbs. The detonator of a simple design allows the terrorist to activate the explosives even when under pressure.

Besides being extremely devastating in terms of casualties, physical damage and psychological impact such attacks are also highly unpredictable. Many factors contribute to

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this high unpredictability. The suicide attackers are extremely motivated either by ideological and/or religious impulses. An *overt attack* i.e. an attack clearly recognizable by law enforcement agencies and other responding agencies is seldom the choice of attackers. In almost all cases a *covert attack* strategy where a carefully disguised dispersal means with no intentional indication, nor a threat or warning being issued is chosen. Until getting to the specific spot where a suicide attacker will operate the explosives, only a highly trained eye would notice anything suspicious. Thus the absence of sufficient empirical data about suicide attacks presents a peculiar decision making problem characterized by information which is incomplete, approximate and vague.

As counter-terrorism policies and strategies are being developed across the globe, prediction of suicide attacks forms an important contribution towards this end. Besides the incomplete information, predicting suicide attacks is typically subjective, because it uses the value judgments of experts, qualitative variables and variables of relative quantification. These elements make this effort extremely uncertain and prevent the tools and procedures based on traditional methods from being fully applied. The decision making environment typically encountered while attempting some prediction of suicide attacks involves imprecise data and their solution involves the use of mathematical principles based on uncertainty and imprecision. Some of these problems are essentially humanistic and thus subjective in nature, while others are objective, yet they are firmly embedded in an imprecise environment. Linguistic terms are used by counter-terror experts and officials but linguistic terms do not hold exact meaning and may be understood differently by different people. The boundaries of a given term are rather subjective, and may also depend on the situation. Linguistic terms therefore cannot be expressed by ordinary set theory; rather, each decision factor is associated with some linguistic term. The thought process involved in the act of decision making in a scenario as defined above is a complex array of streaming possibilities in which a person selects or discards information made available from diverse sources. In doing so one is led by a meaningful analysis of available information and optimal selection out of several apparently equi-efficient decisions. Information is available on the basis of some criteria and the criterion-values are not sharply defined but are vague, incomplete and approximate.

Soft sets introduced by D. Molodtsov [9], is state-of-the-art approach to deal with incomplete knowledge within information systems. However, in practical applications of soft sets, the situation is generally more complex and calls for attributes having non-sharp or fuzzy boundaries, as is the case with prediction of suicide attacks. That is why many authors have contributed towards the fuzzification of the notion of soft set e.g. [1, 3, 4, 5, 8, 11, 13]. Fuzzy soft sets is an attractive extension of soft sets, enriching the latter with extra features to represent uncertainty and vagueness on top of incompleteness. It is now an area of active research in decision making [7] process under vague and approximate conditions.

In this paper we present a fuzzy soft set based decision making model for terror attack prediction for a given collection of cities. The paper is arranged as follows: Section 2 gives a detailed discussion of the factors considered important by human analysts for making prediction of such attacks. After clearly delineating the factors in subsection 2.1 to be considered Section 3.1 first develops a general algorithm using fuzzy soft sets for the prediction. This section besides explaining the working of algorithm and making notes about the computer implementation, presents a detailed illustrative example. Section 4 exhibits the results of simulation results and provides different insights into FSP. Section 5 discusses different aspects of the model; its strengths and weaknesses besides suggesting

possible future enhancements.

2.   Model Construction

Traditional wisdom uses a "low risk / high consequence" strategy for taking security measures. But experience has shown it is not the only and sometimes not even the best counter terror strategy. Scarce resources can be better exploited if a way is found to predict threats according to likelihood, and not just according to the severity of consequences.

Explicitly, a model which attempts to predict suicide attacks should cater for following aspects:

1. Estimate the "attractiveness" of specific cities to terrorist organizations,

2. Identify vulnerabilities to build a portfolio of possible attack locations, and

3. Enable decision makers to concentrate resources on most probable targets.

Construction of a decision making model under the conditions peculiar to suicide attacks should cater both the aspects of information incompleteness and expert's usage of linguistic variables. Linguistic variables are best dealt with Fuzzy Set Theory of Zadeh [14] and information incompleteness is handled by Soft Set Theory of Molodtsov [9]. Both these aspects have been combined in theory of Fuzzy Soft Sets by Maji, Biswas and Roy [8].

We, therefore, proceed first to identify the main factors which in expert opinion may contribute towards the selection of target city by suicide attackers. In the second phase we develop a selection algorithm which takes advantage of the in-built mechanism for quantization of value judgements of counter-terror experts.

2.1.   Potential Factors for Decision Making.   Understanding of the terrorist's target-selection criterion would help us to identify the potential terror attack locations. Therefore, our assessment of which targets are most attractive must be made from the point of view of the terrorist. We enlist following factors to be considered for making a decision:

1. **Maximize the number of casualties:** Their main aim is mass killing and destruction, without regard for their own life or the lives of others. Thus the cities with high population density are more prone to such attacks.

2. **Damage to the civil/military infrastructure:** As the terrorists aim to weaken the civil/military infrastructure or at least they attempt to create an impression that such infrastructures have been subjugated by and large, cities with high concentration of government structures, stand more possibility of attack. To cause such damage of infrastructure, an all alone suicide attack, where a single terrorists explodes himself among masses, is seldom the choice. Instead a variant of suicide attack known as Vehicle-borne improvised explosive device (VBIED) is employed. Typically it is based on a car containing several dozen kilograms or several hundred pounds of explosives (mostly ANFO= ammonium nitrate, diesel oil plus a small booster charge). Truck bombs carrying a larger load of explosives, notably vehicles with up to $8t$ of explosives on board have already been detonated. The vehicle is parked near an area with increased population density (marketplace, shopping center, office building) or driven at high speed against the target (e.g. checkpoint) and

detonated either by remote control or by a suicide driver on board. The type of vehicle used determines largely the number of casualties resulting from the detonation (typically several dozen).

3. **Economic damage potential:** A city where an attack may result in high economic damage becomes a good choice for terrorists involved in a relatively protracted war against established government.

4. **Maximize print and electronic media coverage:** A city with thorough and prompt media coverage is yet another attraction for terror groups. Cities with a lot of movement of high profile personalities is particularly prone to such attacks.

5. **Vicinity of the areas having religious fanaticism, supremacist ideology and/or pronounced anti-government ideology:** A city with geographical and cultural proximity to areas of extremist ideologies is an easy target. Geographical proximity provides easy access to urban center and cultural proximity provides much need camouflage for the suicide attacker.

6. **Day of week:** Day of week has been observed to be of special importance. For example a day of religious gathering of another sect immediately draws the attention of terrorists. Equivalently, in certain countries people of highest military and civil establishment gather for weekly religious services and thus become a very attractive target for suicide bombers.

7. **Post attack hiding:** A city which either due to its high population density or due to its urban planning provides easy hiding places or escape routes is another factor contributing towards the choice of suicide attacker and his accomplices.

8. **Safe heaven:** City with access to a relatively closer safe heaven where development efforts can take place unhindered is very high on terrorist's priority list.

9. **Physical difficulty:** It pertains to different physical obstacles presented to the attacker e.g. security pickets, checkposts, body search spots etc.

10. **Psychological impact:** A city or location generally viewed as the fortress of top leadership and/or establishment (civil/military) carries a very high potential for psychological impact in case of attack. For example such an impact will be very high for capital of a country.

It is important to realize that each of the above mentioned factors is a fuzzy set over the universal set of cities, where membership grade of each city may be decided either quantitatively as in case of population density for factor 1 and/or 7 or by expert's opinion as in factors 4 and 10. Some of the factors may seem overlapping e.g. 5 and 6, but as the prediction attempt suffers from vagueness of linguistic terms and incomplete knowledge both, such an overlap is in fact helpful for passing a judgement based upon plausible reasoning. Moreover factor 5 is a relatively qualitative measure but 6 is quantitatively measurable. Thus each complements the other. A similar argument is extended for the other resembling factors.

Because such a decision making is generally carried out collectively e.g. by a committee of counter-terror officials, it is very much possible that either a certain factor remains undecided or no information could be gathered for it at all. In both cases the factor

has to be eliminated thus modelling the incomplete information aspect of the problem. Secondly, as the linguistic terms used by experts are fuzzy sets we are naturally driven to model this decision making problem using fuzzy soft sets. Therefor we first examine some basic notions from Soft Set Theory and their relevance to our model.

3. Development of Algorithm

As mentioned earlier this prediction problem has two peculiar characteristics:

1. Use of linguistic terms by counter-terror experts in their subjective assessments,

2. Incomplete information and hence the presence of approximate descriptions of different factors of interest.

It is well established now that linguistic vagueness is best tackled by Fuzzy Set Theory [14]. On the other hand, Molodtsov [9] introduced the Theory off Soft Sets to handle the approximate descriptions. Maji, Biswas and Roy [8] combined both these theories as Fuzzy Soft Sets. Naturally this synergy of views is better suited to deal with the problems of linguistic vagueness coupled with approximate descriptions. Thus we intend to develop an algorithm using fuzzy soft sets. For this we first introduce the basic notions of theory:

Definition 3.1. *A pair (F, A) is called a soft set [9] over X, where F is a mapping given by $F : A \rightarrow P(X)$.*
In other words, a soft set over X is a parametrized family of subsets of the universe X. For $\varepsilon \in A$, $F(\varepsilon)$ may be considered as the set of ε-approximate elements of the soft set (F, A). Clearly a soft set is not a set in ordinary sense.

Definition 3.2. *[4] Let X be a universe and E a set of attributes. Then the pair (X, E), called a soft space, is the collection of all soft sets on X with attributes from E.*

Maji *et al.* defined a fuzzy soft set in the following manner:

Definition 3.3. *[8] A pair (Λ, Σ) is called a fuzzy soft set over X, where $\Lambda : \Sigma \rightarrow \widetilde{P}(X)$ is a mapping, $\widetilde{P}(X)$ being the set of all fuzzy sets of X.*

For our model the set of cities is the universal set and the factors of decision making may be viewed as the set E. As the factors for decision making are linguistic variables thus E has to be a set of linguistic variables rendering (X, E) to be a fuzzy soft space. Fuzzy soft space is defined as:

Definition 3.4. *[3] Let X be an universe and E a set of attributes. Then the collection of all fuzzy soft sets over X with attributes from E is called a fuzzy soft class and is denoted as $\widetilde{(X, E)}$.*

Example 3.5. *Let $X = \{a, b, c, d, e\}$ be the set of cities and E, the set of decision factors given as:*

$\varepsilon_1 =$	*High count of casualties*	$\varepsilon_6 =$	*Cultural proximity to terrorists' ethnicity*
$\varepsilon_2 =$	*Damage to infrastructure*	$\varepsilon_7 =$	*Pre attack hiding*
$\varepsilon_3 =$	*Economic damage*	$\varepsilon_8 =$	*Post attack hiding*
$\varepsilon_4 =$	*Media Coverage*	$\varepsilon_9 =$	*Physical security*
$\varepsilon_5 =$	*Distance from terrorist strongholds*	$\varepsilon_{10} =$	*Psychological impact*

Then the assessment of each parameter for every city, as made by a committee of experts, can easily be represented in the form of following fuzzy soft set:

$$(\Lambda, \Sigma) = \left\{ \begin{array}{c} \varepsilon_1 = \{a_{0.7}, b_1, c_1, d_{0.8}, e_1\}, \varepsilon_2 = \{a_1, b_{0.2}, c_{0.9}, d_1, e_{0.2}\}, \varepsilon_3 = \{a_{0.6}, b_{0.2}, c_{0.1}, d_{0.3}, e_{0.8}\}, \\ \varepsilon_4 = \{a_{0.2}, b_{0.4}, c_{0.6}, d_{0.1}, e_{0.4}\}, \varepsilon_5 = \{a_{0.4}, b_{0.8}, c_{0.7}, d_{0.1}, e_{0.2}\}, \varepsilon_6 = \{a_{0.6}, b_{0.3}, c_{0.7}, d_{0.3}, e_{0.9}\}, \\ \varepsilon_7 = \{a_{0.5}, b_{0.9}, c_{0.3}, d_{0.5}, e_{0.5}\}, \varepsilon_8 = \{a_{0.1}, b_1, c_{0.3}, d_{0.5}, e_{0.9}\}, \varepsilon_9 = \{a_{0.8}, b_{0.2}, c_{0.5}, d_1, e_{0.7}\}, \\ \varepsilon_{10} = \{a_{0.5}, b_{0.8}, c_{0.3}, d_1, e_{0.4}\} \end{array} \right\}$$

For a given pair of cities and a given potential factor of prediction, a city having higher membership grade is preferred over the other city. Such pairwise comparisons, if carried out against each decision factor would yield a list of preferences against each decision factor. List of such dominations and subjections for each city may be collected in a similar manner. Heart of the decision making technique is the aggregation of these lists in a meaningful manner. In other words, an aggregation of both lists for a given city translates into a decision measure. Thus the technique aims to exploit comparison of a given city's total dominations vis-a-vis its subjections and magnifying this quotient by the number of equally graded attributes. Using this line of thought we develop algorithm FSP (Fuzzy Soft Prediction) as follows:

3.1. Algorithm.

Name : F**SP**
Input : Set of cities and the factors deemed suitable for prediction.

Output : Sorted list of cities with most probable location at the top.

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1. $X \leftarrow \{\psi_i\}$

2. $E \leftarrow \{\varepsilon_i\}$

3. $(\Lambda, \Xi) \leftarrow \left\{ \varepsilon_i = \Lambda(\varepsilon_i) \mid \Lambda(\varepsilon_i) \in [0,1]^X \right\} \in \widetilde{[X, E]}$

4. **FOR** $(\psi_i, \psi_j) \in X^2$ calculate and store
5. $\quad\quad \rho(\psi_i, \psi_j) = \left\{ \varepsilon_i \in \Xi \mid \Lambda(\psi_i) \geq \Lambda(\psi_j) \right\}$
6. $\quad\quad \chi(\psi_i, \psi_j) = \left\{ \varepsilon_i \in \Xi \mid \Lambda(\psi_i) \leq \Lambda(\psi_j) \right\}$
7. **END FOR**

8. **FOR** $\psi_i \in X$ calculate and store
9. $\quad\quad \nabla(\psi_i) = \sum_{\psi_j \in X} \| \rho(\psi_i, \psi_j) \|$

10. $\quad\quad \Delta(\psi_i) = \sum_{\psi_j \in X} \| \chi(\psi_i, \psi_j) \|$

11. $\quad\quad \Omega(\psi_i) = \sum_{\psi_j \in X} \| \rho(\psi_i, \psi_j) \cap \chi(\psi_i, \psi_j) \|$

12. $\quad\quad \Gamma_1(\psi_i) = \dfrac{\nabla(\psi_i)}{\Delta(\psi_i)} \times \Omega(\psi_i)$
13. **END FOR**

14. $DecisionTable \leftarrow$ **SORT** $(\psi_i, \Gamma_1(\psi_i))$ in descending order of $\Gamma_1(\psi_i)$

15 **OUTPUT** $DecisionTable$

Where $\|.\|$ denotes the cardinality of a crisp set.

3.2. Explanation of FSP. FSP exploits comparison of a given city's total dominations vis-a-vis its subordinations and magnifying this quotient by the number of equally graded attributes. For given two cities, domination is an attribute and/or a decision factor in which one city has a higher grade of membership as compared to the other one. Similarly, subjection is the factor where one city has a lesser membership grade than the other one. In FSP, ρ and χ denote the dominations and subjections, respectively. A full listing of $\rho(\psi_i, \psi_j)$ and $\chi(\psi_i, \psi_j)$ looks like the discernibility matrix of Skowron [12, 10] in Rough Set Theory.

Some explanation of decision measure Γ_1 is in point here. Γ_1 is an equities weighted ratio of dominations and subjections of a city. The role of Ω, total number of attributes having equal membership grades may be considered less useful for certain situations. In such case we may compute Γ_2 given as:

$$\Gamma_2 = \nabla\left(\psi_i\right) - \Delta\left(\psi_i\right).$$

Clearly Γ_2 is simple measure of differentiation or distance between the dominations and subjections of a city. Yet another decision measure is Γ_3 which scales total decision attributes by the equity factor and is given as:

$$\Gamma_3 = \frac{\nabla\left(\psi_i\right) + \Delta\left(\psi_i\right)}{\Omega\left(\psi_i\right)}.$$

In general, $\rho\left(\psi_i, \psi_j\right) + \chi\left(\psi_i, \psi_j\right) \neq \|\Xi\|$. This makes all three measures independent of each other and thus providing three different views of the same decision environment.

3.3. Computer Implementation of FSP. For computer implementation a class named FSS is introduced which specifies the notion of fuzzy soft sets. The basic data structure of FSP is a two dimensional array. This array is constructed in Step 3 from the available sets in Step $1, 2$ and is a member of the class FSS. First part of Step 4 (lines $4-7$) determines the attribute set for each pair of cities where first city dominates others and second part compares for dominated-by pairs. Thus $\rho\left(\psi_i, \psi_j\right)$ is the domination attribute set of ψ_i and $\chi\left(\psi_i, \psi_j\right)$ is the dominated-by attribute set of cities ψ_i and ψ_j. Step 8 (lines $8-11$) collects total number of dominations, subjections and equities for each city ψ_i. Line 12 computes the decision measure Γ_1.

For further explaining the algorithm we give an illustrative example in the following:

Example 3.6. *Since 9/11 in USA, there have been some 247 suicide attacks in Pakistan killing about 3000 innocent lives.. On 12th March 2010, Lahore, one of the five major cities of Pakistan, encountered a spate of nine bombings in a single day killing about 100 people. Out of the nine incidents 4 were suicide attacks. In this example we apply our model of factors and the algorithm FSP to a multi-observer based committee of experts' opinion about the next possible suicide attack in Pakistan. We specifically consider 4 provincial capitals and the national capital. Figure ?? shows map of Pakistan with all the major cities.*

$\psi_1 =$ *Karachi*

$\psi_2 =$ *Lahore*

$\psi_3 =$ *Quetta*

$\psi_4 =$ *Islamabad*

$\psi_5 =$ *Peshawar*
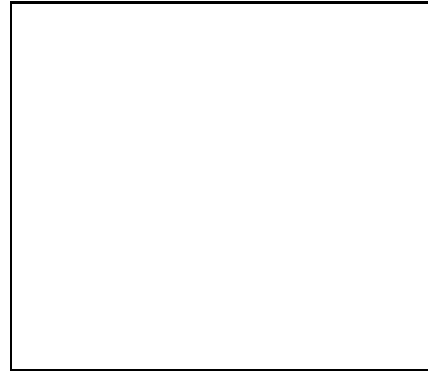
Major cities of Pakistan

Decision parameters as explicated in Section 2.1 have been symbolized as follows:

$\varepsilon_1 =$ *High count of casualties* $\varepsilon_6 =$ *Cultural proximity to terrorists' ethnicity*

$\varepsilon_2 =$ *Damage to infrastructure* $\varepsilon_7 =$ *Pre attack hiding*

$\varepsilon_3 =$ *Economic damage* $\varepsilon_8 =$ *Post attack hiding*

$\varepsilon_4 =$ *Media Coverage* $\varepsilon_9 =$ *Physical security.*

$\varepsilon_5 =$ *Distance from terrorist strongholds* $\varepsilon_{10} =$ *Psychological impact*

Then the assessment of each parameter for every city, as made by a committee of experts, can easily be represented in the form of following fuzzy soft set:

	ε_1	ε_2	ε_3	ε_4	ε_5	ε_6	ε_7	ε_8	ε_9	ε_{10}
ψ_1	0.7	1.0	0.6	0.2	0.4	0.6	0.5	0.1	0.8	0.5
ψ_2	1.0	0.2	0.2	0.4	0.8	0.3	0.9	1.0	0.2	0.8
ψ_3	1.0	0.9	0.1	0.6	0.7	0.7	0.3	0.3	0.5	0.3
ψ_4	0.8	1.0	0.3	0.1	0.1	0.3	0.5	0.5	1.0	1.0
ψ_5	1.0	0.2	0.8	0.4	0.2	0.9	0.5	0.9	0.7	0.4

Tables 1 and 2 on next page, give the dominations and subjections of each city. This permits to calculate cumulative domination, subjection and equity for each particular city as follows:

$$\nabla(\psi_1) = 30, \qquad \Delta(\psi_1) = 33, \qquad \Omega(\psi_1) = 13$$

$$\nabla(\psi_2) = 35, \qquad \Delta(\psi_2) = 30, \qquad \Omega(\psi_2) = 15$$

$$\nabla(\psi_3) = 28, \qquad \Delta(\psi_3) = 34, \qquad \Omega(\psi_3) = 12$$

$$\nabla(\psi_4) = 31, \qquad \Delta(\psi_4) = 33, \qquad \Omega(\psi_4) = 14$$

$$\nabla(\psi_5) = 36, \qquad \Delta(\psi_5) = 30, \qquad \Omega(\psi_5) = 16$$

$\boldsymbol{\rho}\left(\psi_i,\psi_j\right)$	$\boldsymbol{\psi}_1$	$\boldsymbol{\psi}_2$	$\boldsymbol{\psi}_3$	$\boldsymbol{\psi}_4$	$\boldsymbol{\psi}_5$
$\boldsymbol{\psi}_1$	E	$\{\varepsilon_2,\varepsilon_3,\varepsilon_6,\varepsilon_9\}$	$\{\varepsilon_2,\varepsilon_3,\varepsilon_7,\varepsilon_9,\varepsilon_{10}\}$	$\{\varepsilon_2,\varepsilon_3,\varepsilon_4,\varepsilon_5,\varepsilon_6,\varepsilon_7\}$	$\{\varepsilon_2,\varepsilon_5,\varepsilon_7,\varepsilon_9,\varepsilon_{10}\}$
$\boldsymbol{\psi}_2$	$\{\varepsilon_1,\varepsilon_4,\varepsilon_5,\varepsilon_7,\varepsilon_8,\varepsilon_{10}\}$	E	$\{\varepsilon_1,\varepsilon_3,\varepsilon_5,\varepsilon_7,\varepsilon_8,\varepsilon_{10}\}$	$\{\varepsilon_1,\varepsilon_4,\varepsilon_5,\varepsilon_6,\varepsilon_7,\varepsilon_8\}$	$\{\varepsilon_1,\varepsilon_2,\varepsilon_4,\varepsilon_5,\varepsilon_7,\varepsilon_8,\varepsilon_{10}\}$
$\boldsymbol{\psi}_3$	$\{\varepsilon_1,\varepsilon_4,\varepsilon_5,\varepsilon_6,\varepsilon_8\}$	$\{\varepsilon_1,\varepsilon_2,\varepsilon_4,\varepsilon_6,\varepsilon_9\}$	E	$\{\varepsilon_1,\varepsilon_4,\varepsilon_5,\varepsilon_6\}$	$\{\varepsilon_1,\varepsilon_2,\varepsilon_4,\varepsilon_5\}$
$\boldsymbol{\psi}_4$	$\{\varepsilon_1,\varepsilon_2,\varepsilon_7,\varepsilon_8,\varepsilon_9,\varepsilon_{10}\}$	$\{\varepsilon_2,\varepsilon_3,\varepsilon_6,\varepsilon_9,\varepsilon_{10}\}$	$\{\varepsilon_2,\varepsilon_3,\varepsilon_7,\varepsilon_8,\varepsilon_9,\varepsilon_{10}\}$	E	$\{\varepsilon_2,\varepsilon_7,\varepsilon_9,\varepsilon_{10}\}$
$\boldsymbol{\psi}_5$	$\{\varepsilon_1,\varepsilon_3,\varepsilon_4,\varepsilon_6,\varepsilon_7,\varepsilon_8\}$	$\{\varepsilon_1,\varepsilon_2,\varepsilon_3,\varepsilon_4,\varepsilon_6,\varepsilon_9\}$	$\{\varepsilon_1,\varepsilon_3,\varepsilon_6,\varepsilon_7,\varepsilon_8,\varepsilon_9,\varepsilon_{10}\}$	$\{\varepsilon_1,\varepsilon_3,\varepsilon_4,\varepsilon_5,\varepsilon_6,\varepsilon_7,\varepsilon_8\}$	E

Table 1: Table of dominations

$\boldsymbol{\chi}\left(\psi_i,\psi_j\right)$	$\boldsymbol{\psi}_1$	$\boldsymbol{\psi}_2$	$\boldsymbol{\psi}_3$	$\boldsymbol{\psi}_4$	$\boldsymbol{\psi}_5$
$\boldsymbol{\psi}_1$	E	$\{\varepsilon_1,\varepsilon_4,\varepsilon_5,\varepsilon_7,\varepsilon_8,\varepsilon_{10}\}$	$\{\varepsilon_1,\varepsilon_4,\varepsilon_5,\varepsilon_6,\varepsilon_8\}$	$\{\varepsilon_1,\varepsilon_2,\varepsilon_7,\varepsilon_8,\varepsilon_9,\varepsilon_{10}\}$	$\{\varepsilon_1,\varepsilon_3,\varepsilon_4,\varepsilon_6,\varepsilon_7,\varepsilon_8\}$
$\boldsymbol{\psi}_2$	$\{\varepsilon_2,\varepsilon_3,\varepsilon_6,\varepsilon_9\}$	E	$\{\varepsilon_1,\varepsilon_2,\varepsilon_4,\varepsilon_6,\varepsilon_9\}$	$\{\varepsilon_2,\varepsilon_3,\varepsilon_6,\varepsilon_9,\varepsilon_{10}\}$	$\{\varepsilon_1,\varepsilon_2,\varepsilon_3,\varepsilon_4,\varepsilon_6,\varepsilon_9\}$
$\boldsymbol{\psi}_3$	$\{\varepsilon_2,\varepsilon_3,\varepsilon_7,\varepsilon_9,\varepsilon_{10}\}$	$\{\varepsilon_1,\varepsilon_3,\varepsilon_5,\varepsilon_7,\varepsilon_8,\varepsilon_{10}\}$	E	$\{\varepsilon_2,\varepsilon_3,\varepsilon_7,\varepsilon_8,\varepsilon_9,\varepsilon_{10}\}$	$\{\varepsilon_1,\varepsilon_3,\varepsilon_6,\varepsilon_7,\varepsilon_8,\varepsilon_9,\varepsilon_{10}\}$
$\boldsymbol{\psi}_4$	$\{\varepsilon_2,\varepsilon_3,\varepsilon_4,\varepsilon_5,\varepsilon_6,\varepsilon_7\}$	$\{\varepsilon_1,\varepsilon_4,\varepsilon_5,\varepsilon_6,\varepsilon_7,\varepsilon_8\}$	$\{\varepsilon_1,\varepsilon_4,\varepsilon_5,\varepsilon_6\}$	E	$\{\varepsilon_1,\varepsilon_3,\varepsilon_4,\varepsilon_5,\varepsilon_6,\varepsilon_7,\varepsilon_8\}$
$\boldsymbol{\psi}_5$	$\{\varepsilon_2,\varepsilon_5,\varepsilon_7,\varepsilon_9,\varepsilon_{10}\}$	$\{\varepsilon_1,\varepsilon_2,\varepsilon_4,\varepsilon_5,\varepsilon_7,\varepsilon_8,\varepsilon_{10}\}$	$\{\varepsilon_1,\varepsilon_2,\varepsilon_4,\varepsilon_5\}$	$\{\varepsilon_2,\varepsilon_7,\varepsilon_9,\varepsilon_{10}\}$	E

Table 2: Table of subjections

Calculating Γ_1, Γ_2, Γ_3 and plotting the three possibility distributions we get

	Γ_1	Γ_2	Γ_3
ψ_1	11.8	-3	4.9
ψ_2	17.5	5	4.33
ψ_3	9.9	-6	5.17
ψ_4	13.2	-2	4.57
ψ_5	19.2	6	4.12

Sorting decision table under Γ_1 we have

	Γ_1	Γ_2	Γ_3
ψ_5	19.2	6	4.12
ψ_2	17.5	5	4.33
ψ_4	13.2	-2	4.57
ψ_1	11.8	-3	4.9
ψ_3	9.9	-6	5.17

Thus the city of Peshawar (ψ_5) is the most likely next target of a suicide attack according to the given expert assessment.

4. Simulation Results

It is imperative to estimate the bias (if any) of FSP. Using Borland's C++ compiler on an Intel Pentium dual core machine under Windows operating system, a sample run of 1000 scenarios was simulated for 10 cities with 20 factors of decision. The frequency of each city being most probable target is counted as:

	ψ_1	ψ_2	ψ_3	ψ_4	ψ_5	ψ_6	ψ_7	ψ_8	ψ_9	ψ_{10}
Γ_1	103	101	95	83	98	103	108	98	107	118
Γ_2	102	100	96	82	101	91	123	118	109	109
Γ_3	114	122	105	131	119	117	146	128	117	130

Histogram of decision experiments is shown below exhibiting a non-biased evenly distributed distribution for all cities:

For certain scenarios higher number of ties may be considered weakness of a decision measure. This helps to choose between Γ_1, Γ_2 and Γ_3. Following is a count of ties in a sample run of the simulation:

Γ_1	Γ_2	Γ_3
246	440	2129

Number of ties in Γ_1, Γ_2 and Γ_3.

5. Discussion

5.1. Limitations of Decision Making Factors.   The possibility of a suicide attack on a particular target is dependant not only on the characteristics of the target—its symbolic or strategic value and its vulnerabilities— but also on the ambition, capabilities, and sensitivities of the relevant terrorist organizations. This model as, based on a generic analysis; in order to be truly effective, it would require far more parameters than those shown—an analysis that is beyond the scope of this paper. We have attempted to establish criteria for judging which attack scenarios might prove "attractive" to the terrorist groups that might be interested in attacking the venue in question.

The value of the model discussed here lies not in its ability to reveal new information, but rather in its usefulness as a planning and decision making aid: a means to visualize data so that trends may be readily apparent where they might otherwise have been lost in a heap of data. Naturally, the resulting numbers are only as good as the information that goes into the model. In effect, the model should be viewed as merely a template for better organizing our knowledge; without that knowledge, the template is empty of all content. As our judgments regarding the affinities and sensitivities of these groups are necessarily approximate and since these input parameters are associated with significant uncertainties, the resulting risk assessment is also subject to large uncertainties due to error propagation. Thus when based on reliable information, the model is a very useful tool for knowledge management, data visualization and risk assessment.

5.2. Possible Future Enhancements.   Following directions for future research may be identified:

1. This method can be further enhanced to include data-mining abilities. This raw data would provide the basis for a continual reevaluation of the organizational factors of interest that enter into the equation. The result will be a dynamic threat assessment apparatus which could be programmed to "flag" certain types of venues and cities when the relevant threat indices reach a critical level. The end product would be applicable to governments, installation security, public transport officials, and a host of other sectors that could be targeted by terrorists.

2. The algorithm in its present form is of order is of following order $O\left(2^n\right)$ of complexity as for n cities in X computer has to carry out exactly 2^n comparisons due to first loop i.e.

$$FirstLoop\left(comparisons\right) + SecondLoop\left(additions\right) = 2^n + n.$$

   In future we shall endeavour to optimize complexity-efficiency profile of FSP.

3. Representation of knowledge in the form of a discernibility matrix has been found of great advantages, in particular it enables simple computation of the core, reducts and other concepts in Rough Set Theory [10, 12]. Our computation of $\rho\left(\psi_i, \psi_j\right)$ and $\chi\left(\psi_i, \psi_j\right)$ closely resemble a discernibility matrix. Research efforts may fruitfully be employed to exploit this resemblance.

Conclusion 5.1. *For a given collection of cities we present a model for predicting occurrence of suicide attacks. The model has been developed in two parts. Factors which affect the prediction oriented decision making have been considered in first part. Considering incomplete information and the use of linguistic terms by experts, as two characteristic parts of the prediction problem we use the Theory of Fuzzy Soft Sets. The theory is still in its embryonic stage and has a rich potential to solve such typically ill-posed decision problems. Second part of the model is an algorithm vz. FSP which takes the assessment of factors given in Part 1 as its input and produces a possibility profile of cities likely to receive the accident. Algorithm has been illustrated by an example solved in detail. Example considers the case of Pakistan's five big cities and their relevant factors for prediction making. Simulation results for the algorithm have been presented which give insight into the strengths and weaknesses of FSP.*

Three different decision making measures have been simulated and compared in our discussion. We also point a few possible directions for future work in the direction of this paper. Our simulation results show that decision measure Γ_1 has far less bias as compared to other measures. Though there can be scenarios where the other two measures are found more useful.

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